A Dynamic and Context-aware Model of Knowledge Transfer and Learning using a Decision Making Perspective

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Abstract: All the processes taking place in a social network are characterised by dynamism, complexity and context-dependence. Processes involving knowledge have these features. The intrinsic characteristic of knowledge is represented by the value that it can generate in a network, due to its constant and continuous rate of growth. In a heterogeneous network not all the nodes have similar knowledge levels. Furthermore, not all the connections have the same importance. In order to consider knowledge as a resource and not as an obstacle, it is admittable that nodes can decide individually with whom transfer knowledge. Using a context-aware decision making perspective and considering each single node as a decision maker that has to decide in a particular context whether accept the transfer or not, it will be helpful to understand how and why certain mechanisms and behavioural patterns arise.

In this paper, the proposed model considers the process of knowledge transfer as a decision making one, where each alternative, one of the nodes neighbor that wants to transfer knowledge, has an evaluation on the basis of two criteria, knowledge distance and confidence. Their values are dynamically updated at each time step on the basis of the quality of the knowledge transferred.

1 INTRODUCTION

In the era of innovation and technology advance data, information and knowledge play a central role in any process regarding the development and the progress level of a society. The main aim for all the countries is to become "knowledge societies" in continuous development thanks to the limitless knowledge growth which generate incommensurable value (Fedoroff, 2012). Furthermore, thanks to the evolution of the Information and Communication Technology (ICT) there are no limits on when, where and how knowledge has to be transferred among individuals. Looking much more in detail, each individual decides (Guy et al., 2015) and acts within a social network, characterised by a dynamic, ubiquitous, complex and context-dependent nature. For each entity (Cioffi-Revilla, 2013), representing the network node, the consideration of who is connected to whom as well as the structure of the network have an important effect on the type of information passed, on its quantity and on the efficiency of the process itself (Cowan and Jonard, 2004). Furthermore, by taking into account the role of the context, the importance of each single relation (Barrat et al., 2004) and the structure of the network itself can vary depending on the considered context. In fact it is different the level of awareness held by the single node.

In this paper we consider a process of knowledge transfer using a context-aware decision making perspective (Giacchi et al., 2014) in which, before accepting or rejecting knowledge from one of its neighbors, a network node judges if its evaluation satisfies some criteria, i. e. knowledge distance and confidence, and, after that, it decides what to do. If the process takes place and the receiver node accepts the transfer, it will perform a control on what it has just accepted on the basis of three parameters. If the control result is positive, the receiver node will increase its confidence in the sender node. On the contrary case it will decrease its confidence and it will learn only a percentage of the received knowledge.

The paper is organized as follows. Section 2 gives a brief overview on knowledge and its typical processes and on context-aware applications. Section 3 is the main part of the work, where the whole process involving knowledge by exploiting a decision mak-

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ing perspective is explained. The results are shown in Section 4. Section 5 collects conclusions and reports future directions of research.

2 RELATED WORKS

2.1 Knowledge and Its Processes within a Network

Knowledge guides every process in a network. Two of the main features of the processes that involve knowledge are complexity and dynamism, which are related to the property of the processes environment itself. Between the definition of knowledge and information there is a substantial difference, even if in some cases they are used indifferently. Information is compared to a "flow of messages" (Nonaka, 1994) that can contribute to shape an individual outlook or insight (Davenport and Prusak, 1998). Knowledge instead "*is a fluid mix of framed experience, values, contextual information, and expert insight that provides a framework for evaluating and incorporating new experiences and information*" (Davenport and Prusak, 1998). In the Knowledge Management field it is also important to distinguish between two categories of knowledge: tacit and explicit. Tacit knowledge was firstly introduced in 1967 (Polanyi, 1967) and it refers to the knowledge that is difficult to express and transmit because it depends on human and personal qualities of the individual, that make it not easily transferable among individuals (Nonaka, 1994). On the contrary explicit knowledge is easily formalized, codified and transmitted in a formal and systematic language (Nonaka, 1994; Brown and Duguid, 1991). It can be found in databases, manuals and documents.

In a network as well as among different individuals, knowledge can be shared, transferred and exchanged (Graham et al., 2006). Knowledge sharing corresponds to the provision of information and know-how of a task among individuals inside and outside a group (Cummings, 2004). Knowledge transfer includes two phases: the sharing of knowledge from a source and its acquisition from a recipient. Knowledge exchange involves both knowledge sharing through which a source provides knowledge and knowledge seeking, where a receiver searches knowledge from sources (Wang and Noe, 2010). Several works have analysed the processes involving knowledge in a network by using different perspectives (Lambiotte and Panzarasa, 2009; Tasselli, 2015; Hatak and Roessl, 2015).

2.2 Context-aware Applications

As previously stated, the third feature of a process involving knowledge is its context-dependance. It is a consequence of the environment in which each process takes place, as for the other two features. Until now there is not a standard definition of context, but several attempts have been made. In fact, several and different definitions are present in the scientific literature, but most of researchers agree to consider context as *"any information that can be used to characterise the situation of an entity. An entity is a person, place or object that is considered relevant to the interaction between a user and an application, including the user and applications themselves"* (Abowd et al., 1999). As a consequence of the information held, different entities can have, for example, contrasting perception of the same circumstance. Consequently, if a system uses context to provide information and/or services to the user, it can be defined as context-aware (Abowd et al., 1999). Accordingly, the ability of a system to discover and to react to changes in the environment it is in, is defined "context-awareness" (Schilit and Theimer, 1994).

Nowadays context-aware applications are used in several fields thanks also to their integration with sensors and geographic information systems. In such a way, the services that it is possible to provide are more specific, advanced and cover several sectors (Guermah et al., 2013; Gui et al., 2011).

3 MODEL DESCRIPTION

A model of knowledge transfer is characterised by three main features i. e. the dynamism, the complexity and the context-dependence. The model presented in this paper looks at the knowledge transfer process as a decision making one, taking as reference points two models reported in the scientific literature (Cowan and Jonard, 2004; Luo et al., 2015). We assume that the process of knowledge transfer can be considered as an individual decision making process where each node, part of a network, is involved in a process of knowledge transfer. In particular, it has to decide whether to accept or not knowledge coming from its neighboring nodes which represent the set of alternatives. In a first stage, it has been chosen to take into account only a single process regarding explicit knowledge, due to its unambiguous and clear characteristics of easy codification and transmission.

For the description of our model we shall use the following notation:

- $N = \{n_1, \ldots, n_i, \ldots, n_m\}$, a finite set of nodes;

- $K = \{K_1, \ldots, K_k, \ldots, K_p\}$, a finite set of contexts;
- $v_i^{K_k}(t) = \left\{v_{i,1}^{K_k}(t), \ldots, v_{i,l}^{K_k}(t), \ldots, v_{i,q}^{K_k}(t)\right\}$, the knowledge vector of the node n_i with respect to the q categories and the context K_k at time t;
- $A_{ij}^{K_k} = \left\{a_{ij}^{K_k}\right\}$, the adjacency matrix representing the network in the context K_k. $a_{ij}^{K_k} = \{0, 1\}$ is each single element which identifies if the link between nodes n_i and n_j is present or not;
- $N_i^{K_k} = \left\{n_j \in N : a_{i,j}^{K_k} = 1\right\}$, the set of nodes linked to node n_i in the context K_k. It represents the set of alternatives for node n_i.

As explained in Section 1 one of the context roles is to characterise and differentiate the strength of each node's connection and the structure of the network itself. In order to do so, we consider the vector of weights $w_i^{K_k} = \left(w_{i,1}^{K_k}, \ldots, w_{i,j}^{K_k}, w_{i,m}^{K_k}\right)$, where each element $w_{i,j}^{K_k}$ represents the strength of the relation between node n_i and node n_j in the context K_k. $w_{i,j}^{K_k}$ can be different from $w_{j,i}^{K_k}$ ($w_{i,j}^{K_k} \neq w_{j,i}^{K_k}$). With respect to the previous models, the decision whether to accept or not the knowledge offered from another node in the network is based on two criteria i. e. knowledge distance and confidence. Each alternative $n_j \in N_i^{K_k}$ has an evaluation on each of the two criteria. The first criterion is defined as:

$$d_{ij,l}^{K_k}(t) = v_{j,l}^{K_k}(t) - v_{i,l}^{K_k}(t) \tag{1}$$

This distance represents the quantity of knowledge that node n_i could receive from node n_j in the category l within the considered context. The knowledge distance can be considered the expression of the knowledge heterogeneity of the two nodes involved in the process. If there is a high knowledge gap between two network nodes (high heterogeneity), node n_i could have no gain from the knowledge received from node n_j (Luo et al., 2015).

The second criterion is represented by the confidence. In particular, at the moment, we suppose that the confidence $c_{i,j}^{K_k}$ that the node n_i has in node n_j in the context K_k is defined as:

$$c_{i,j}^{K_k}(t) = \frac{w_{i,j}^{K_k}(t) + J_{i,j}^{K_k}}{2} \tag{2}$$

where $w_{i,j}^{K_k}(t)$ is the weight that node n_i gives to the link with node n_j. $J_{i,j}^{K_k}$ is the Jaccard similarity (Jaccard, 1901) i. e. an expression of the concept of homophily (Lazarsfeld et al., 1954; Di Stefano et al., 2015), calculated as the ratio of the common neighbors of the nodes n_i and n_j to the number of nodes that are neighbors of at least one between n_i and n_j. The greater the confidence that n_i has in n_j, the more susceptible node n_i is to learn from node n_j (Pentland, 2014). In order to ensure that the knowledge transfer process to take place, the evaluation of alternative n_j belonging to the set $N_i^{K_k}$ in each of the two decision criteria has to satisfy at the same time this two condition:

- $d_{ij,l}^{K_k}(t) \leq d$, that is the knowledge distance has to be under a knowledge distance threshold;
- $c_{i,j}^{K_k}(t) \geq c$, that is the confidence has to be over a certain confidence threshold.

Among the set of nodes satisfying at the same time both conditions related to the two criteria, node n_i for each knowledge category will accept knowledge from the one that can give it the greatest amount of knowledge. The knowledge level of node n_i in the category l in the context K_k will become:

$$v_{i,l}^{K_k}(t+1) = v_{i,l}^{K_k}(t) + max_{n_j \in N_i^{K_k}}((\lambda_{ij,l}^{K_k}(v_{j,l}^{K_k}(t) - v_{i,l}^{K_k}(t))) \tag{3}$$

where:

- $v_{i,l}^{K_k}(t)$ ($v_{j,l}^{K_k}(t)$) represents the knowledge level of node n_i (n_j) in category l in the context K_k at time t;
- $\lambda_{ij,l}^{K_k}$ represents the absorptive capacity of node n_i with respect to the knowledge received from node n_j in the category l. In this model, we assume that the value of $\lambda_{ij,l}^{K_k}$ is strictly related to the risk attitude of node n_i (Kahneman and Tversky, 1979). As shown in Figure 1, we assume that the process of knowledge transfer is located into the region identified by the red box i. e. the greater the amount of knowledge received by node n_i ($x_1 < x_2$) the greater its utility is ($u(x_1) < u(x_2)$) but the greater its risk aversion is with the increasing quantity of knowledge that a node n_j wants to transfer to node n_i (Binswanger, 1980; Holt and Laury, 2002), in order, for example, not to imperil its security (La Corte et al., 2011).

Hence, the value of $\lambda_{ij,l}^{K_k}$ will be a function of the knowledge distance and it can be expressed as:

$$\lambda_{ij,l}^{K_k}(t) = \frac{1}{\exp^{d_{ij,l}^{K_k}}(t)} \tag{4}$$

According to this formulation, the values that $\lambda_{ij,l}^{K_k}(t)$ can assume are included in the set $\left[\frac{1}{\exp^d}; 1\right]$. In such a way if the values are closer to $\frac{1}{\exp^d}$ it means that node n_i is more risk averse and

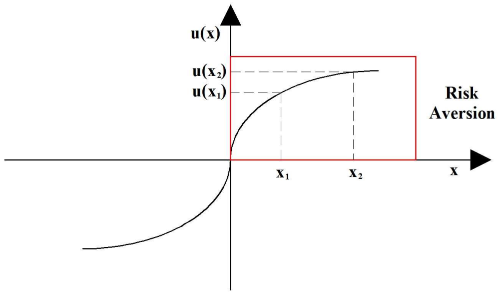


Figure 1: Utility function in the prospect theory.

then it assimilates less knowledge, than a node that has a value of $\lambda_{ij,c}^{K_k}(t)$ near to 1 that it assimilates more knowledge.

After that, node n_i will make a control on the received knowledge before learning it, that is the evaluation of its quality on the basis of three criteria (Bukowitz and Williams, 2000; Suwa et al., 1982):

- Accessibility, defined as the capability for the receiver node to easily access to the whole knowledge that it has received;
- Guidance, defined as the knowledge property to be divided into topics or domain in order to avoid an information overload;
- Completeness, defined as the knowledge property to contain all the information requested by the receiver node

If the evaluation of the received knowledge exceeds the quality threshold in at least two of the three criteria, node n_i will learn and assimilate knowledge at all. Furthermore, it will increase the weight and then the confidence in node n_j. On the contrary, node n_i will learn only the 20% of the received knowledge and its confidence in node n_j will decrease. In particular, the weights will increase or decrease as follows:

$$w_{i,j}^{K_k}(t+1) = w_{i,j}^{K_k}(t) \pm \sum_{l=1}^{q} \frac{d_{ij,l}^{K_k}}{100} \quad (5)$$

In the proposed model every network node thinks, acts and decides in several and different contexts that are related each other, modifying the measures that characterise the network. In order to calculate and analyse this correlation, we consider each context as a plane of the space and, taking one as a reference plane, the greater the cosine of the angle between two planes is the more similar they are, on the contrary they are less similar. In Figure 2 the correlation among contexts is shown. Furthermore, its dynamic nature is shown, because the reference context and the position of each plane in the space can vary at different time instants.

4 RESULTS AND DISCUSSION

In this section, we analyse the model performance under different simulation hypothesis, considering for example a scenario in which network nodes have to accept knowledge, defined in Section 2, from their neighbors through emails, social networks or via a face-to-face contacts. We compare the results of two networks that follow the first one the Erdös-Rényi model (Erdös and Rényi, 1959) and the second one the Barabási-Albert model (Barabási and Albert, 1999). Both networks are characterised by the following parameters:

- $m = 500$, the number of nodes composing the network;
- the number of categories q is set to 5;
- the distance threshold is set to 0.2;
- the confidence threshold is set to 0.4;
- the quality threshold is set to 0.5;
- each knowledge category has a fixed evaluation on each single quality parameter i.e. accessibility, guidance and completeness;
- the network configuration does not change over time i.e. the number and the mutual connections do not change;
- only one context K_k has been considered ;
- for the Erdös-Rényi model, we consider a probability $p = 0.3$, where p represents the probability of having a connection between two nodes;
- we suppose that the Barabási-Albert model follows a law of linear preferential attachment.

In the two cases, we use two measures in order to evaluate in which manner the two network models perform. The two measures are:

- the knowledge percentage held by node n_i at time $t+T$ in the context K_k:

$$v_i^{K_k}(t+T) = \frac{\sum_{l=1}^{q}(v_{i,l}^{K_k}(t+T) - v_{i,l}^{K_k}(t))}{q \cdot 100} \quad (6)$$

- the confidence value of each node at time $t+T$ in the context K_k:

$$c_i^{K_k}(t+T) = \frac{\sum_{i \neq j}(c_{i,j}^{K_k}(t+T) - c_{i,j}^{K_k}(t))}{|N|} \quad (7)$$

In order to show the dynamism of the proposed model, considering the Erdös-Rényi network configuration, in Figures 3 and 4, the knowledge level for each node of the network in all the categories q and the confidence level at time t have been reported, respectively. The first value is calculated as the ratio of

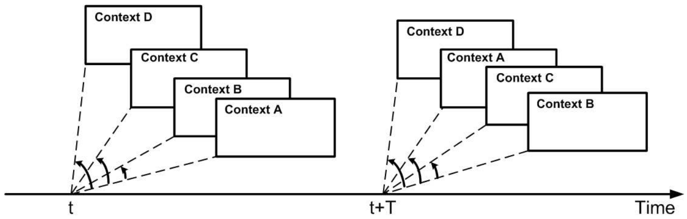


Figure 2: Contexts correlation in the space.

the sum of the knowledge level held by node n_i in all the categories to the number of categories. Instead, the second one is calculated as the ratio of the sum of the confidence of all the relations of node n_i to the total number of nodes of set N. Each node is colored according to the knowledge and confidence level held at time t and the colors association is shown in Table 1 and in Table 2.

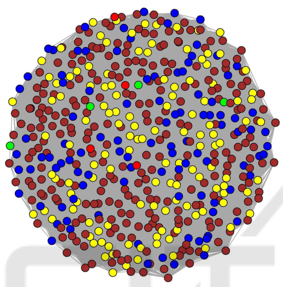


Figure 3: Starting Knowledge Level for the network nodes.

Table 1: Colors associated to the nodes depending on the knowledge level held at time t.

Starting Knowledge Level (z)	Color
$0 \leq z \leq 0.2$	Red
$0.2 < z \leq 0.4$	Yellow
$0.4 < z \leq 0.6$	Brown
$0.6 < z \leq 0.8$	Blue
$0.8 < z \leq 1$	Green

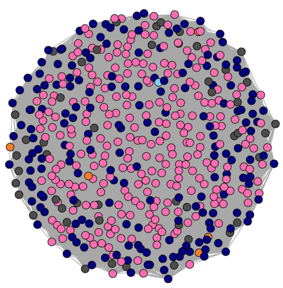


Figure 4: Starting Confidence Level for the network nodes.

Considering Equation 6, in order to track the dynamics of the knowledge transfer process, we take into account 3 time instants, that are $t+5$, $t+10$ and $t+15$. In Figure 5, each node is colored according to the percentage of increased knowledge that it holds after each $t+T$ time instants, and, in particular, the colors associated to each percentage interval are shown in Table 3.

Table 2: Colors associated to the nodes depending on the confidence level that it is associated for each node at time t.

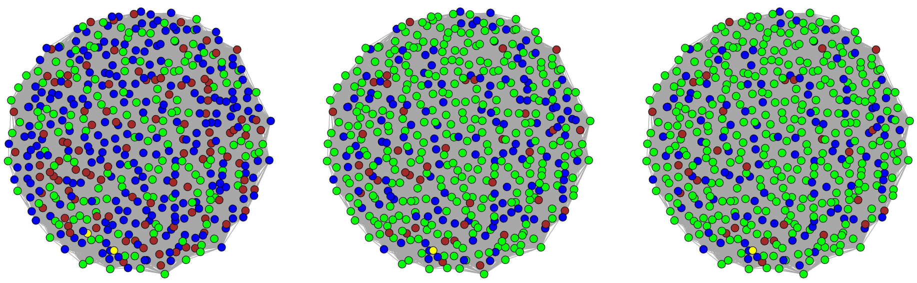
Starting Confidence Level (s)	Color
$s \leq 0.07$	Light Blue
$0.07 < s \leq 0.08$	Orange
$0.08 < s \leq 0.09$	Grey
$0.09 < s \leq 0.1$	Blue
$s > 0.1$	Pink

Table 3: Colors associated to the nodes depending on the knowledge percentage held.

Knowledge Percentage ($v_i^{K_k}(t+T)$)	Color
$v_i^{K_k}(t+T) = 0$	Red
$0 < v_i^{K_k}(t+T) \leq 0.016$	Yellow
$0.016 < v_i^{K_k}(t+T) \leq 0.036$	Brown
$0.036 < v_i^{K_k}(t+T) \leq 0.06$	Blue
$0.06 < v_i^{K_k}(t+T) \leq 1$	Green

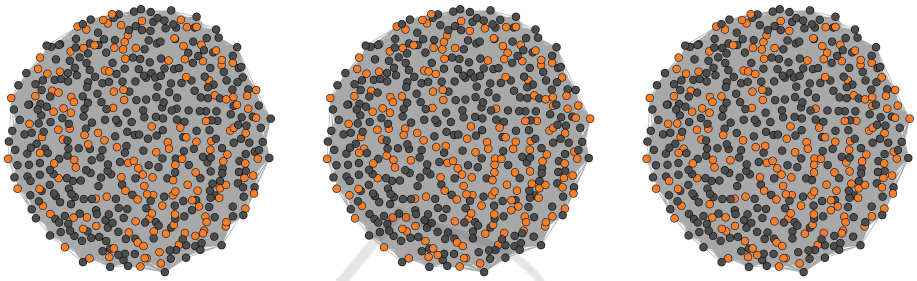
As it is possible to see by observing Figure 5 and considering different time instants, the level of knowledge of each node changes dynamically. In particular it increases, but due to the static nature of the network, that is no nodes are added or removed, after a certain time instant the process of knowledge transfer will stop. What we would like to highlight is the progressive development of the knowledge level in the network, due both to the risk aversion of each node, through which the more it receives the more it is adverse to assimilate, and the quality control of the received knowledge introduced in this model. Considering Equation 7 and the time instants $t+5$, $t+10$ and $t+15$, Figure 6 reports how dynamically the confidence level changes over time. Each node is colored according to its increasing or decreasing value of confidence with respect to the other network nodes. The colors are associated as shown in Table 4.

The reason of the dynamical behaviour of the



(a) Time $t+5$ (b) Time $t+10$ (c) Time $t+15$

Figure 5: Dynamic of the knowledge transfer process for the Erdös-Rényi model.



(a) Time $t+5$ (b) Time $t+10$ (c) Time $t+15$

Figure 6: Dynamic of the confidence level for each node in the network following the Erdös-Rényi model.

Table 4: Colors associated to the nodes depending on their confidence values.

Confidence Value ($c_{i,j}^{K_k}(t+T)$)	Color
$s=0$	Light Blue
$s>0$	Orange
$s<0$	Grey

increasing/decreasing confidence level is that, the knowledge of the categories that they transferred in a first period was not of a good quality, but after a certain time interval they start to transfer knowledge in other categories whose quality is good, or viceversa.

As for the Erdös-Rényi model, now we will show how, using a Barabási-Albert model, the network structure will affect the knowledge dynamics. In Figure 7 and 8 it is reported the knowledge and confidence level for the network at time t and each node is colored according to Tables 1 and 2.

Due to the fact that not all the nodes are connected to each other and there are nodes with a very few number of links, the starting confidence level is really low, compared to the previous model, in fact for all the nodes it is under the value of 0.07. At the same time instants, the dynamics of the two network models are different because the level of knowledge increases slower than the previous case, as shown in Figure 9. This is due to the structure of the network itself. In fact, in this case the colors associated are different, because in order to appreciate the knowledge increasing we have to change the scale (The higher increasing percentage is 0.00001%).

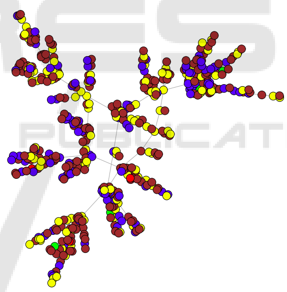


Figure 7: Level of Knowledge for the network nodes.

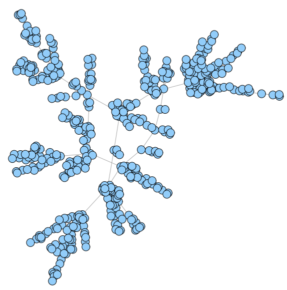
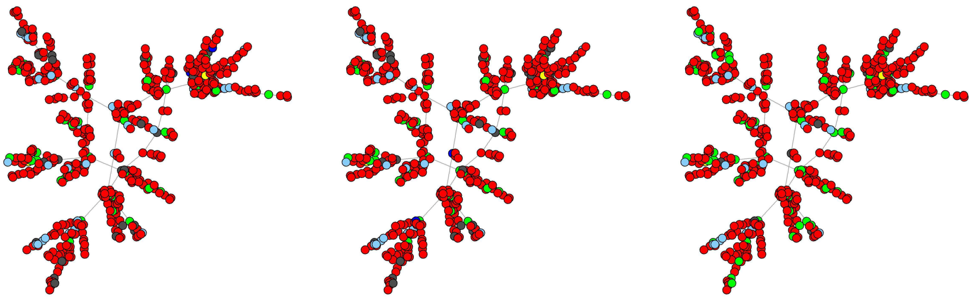


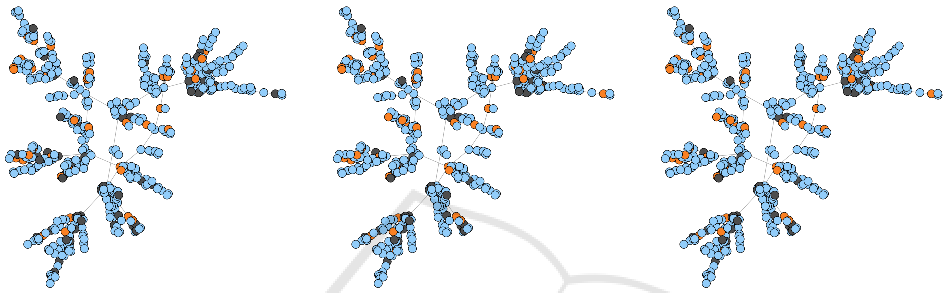
Figure 8: Level of Confidence for the network nodes.

Similarly to what happens for the knowledge,



(a) Time $t+5$ (b) Time $t+10$ (c) Time $t+15$

Figure 9: Dynamic of the knowledge transfer process for the Barabási-Albert model.



(a) Time $t+5$ (b) Time $t+10$ (c) Time $t+15$

Figure 10: Dynamic of the confidence level for each node in the network following the Barabási-Albert model.

the mechanism of increasing/decreasing of the confidence level is not so evident due to the high centrality held by a little percentage of nodes.

From these results, it is observable that in a more distributed network configuration the dynamics of knowledge diffusion and of the confidence level are observable much more than a centralized structure.

5 CONCLUSIONS AND FUTURE WORKS

Nowadays, data, information and knowledge represent the core part of the network. The analysis of their diffusion's patterns could be helpful to predict and study phenomena and node's behaviour within the network itself. Furthermore, by considering the context as a variable that affects the network structure and the knowledge held by the single node, adds further complexity and dynamism to a process that already has these features. Compared to the previous works, the main aim of the model presented in this paper is to understand why a node, part of a network and considered as a decision maker, decides whether to accept or not knowledge from its neighboring nodes that represent the set of alternatives. The decision is based on the evaluation of each alternative based on two decision criteria, the knowledge distance and the confidence. In such a way, the structure of the network and, in particular, the typology of the node's connections, both depending on the context, affect the node's decision. This process is also characterised by a mechanism of confidence increasing and decreasing, that occurs after the evaluation of the quality of the knowledge received at each time instant and which adds dynamism to the model. In this sense, this work is a first attempt to investigate how the introduction of a context-aware decision making perspective in the processes involving knowledge may vary its diffusion's pattern.

Future works will be focused on analysing the process involving knowledge with the introduction of other decision criteria, considering different contexts and adding or removing links in the network. In such a way different decision making scenarios and their impact on the knowledge diffusion will be taken into account.

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REFERENCES

Abowd, G., Dey, A., Brown, P., Davies, N., Smith, M., and Steggles, P. (1999). Towards a better understanding of context and context-awareness. In Gellersen, H.-W., editor, *Handheld and Ubiquitous Computing, LNCS 1707*, pages 304–307, Berlin Heidelberg. Springer.

Barabási, A. and Albert, R. (1999). Emergence of scaling in random networks. *Science*, 286(5439):509–512.

Barrat, A., Barthelemy, M., Pastor-Satorras, R., and Vespignani, A. (2004). The architecture of complex weighted networks. *Proceedings of the National Academy of Sciences of the United States of America*, 101(11):3747–3752.

Binswanger, H. P. (1980). Attitudes toward risk: Experimental measurement in rural india. *American journal of agricultural economics*, 62(3):395–407.

Brown, J. S. and Duguid, P. (1991). Organizational learning and communities-of-practice: Toward a unified view of working, learning, and innovation. *Organization science*, 2(1):40–57.

Bukowitz, W. R. and Williams, R. L.(2000). *The knowledge management fieldbook*. Financial Times/Prentice Hall

Cioffi-Revilla, C. (2013). *Introduction to Computational Social Science: Principles and Applications*. Springer, Science & Business Media.

Cowan, R. and Jonard, N. (2004). Network structure and the diffusion of knowledge. *Journal of economic Dynamics and Control*, 28(8):1557–1575.

Cummings, J. N. (2004). Work groups, structural diversity, and knowledge sharing in a global organization. *Management science*, 50(3):352–364.

Davenport, T. H. and Prusak, L. (1998). *Working knowledge: How organizations manage what they know*. Harvard Business Press.

Di Stefano, A., Scatà, M., La Corte, A., Liò, P., Catania, E., Guardo, E., and Pagano, S. (2015). Quantifying the Role of Homophily in Human Cooperation Using Multiplex Evolutionary Game Theory. *PloS one*, 10(10):e0140646.

Erdös, P. and Rényi, A. (1959). On random graphs I. *Publ. Math. Debrecen*, 6:290–297.

Fedoroff, N. V. (2012). The global knowledge society. *Science*, 335:503.

Giacchi, E., Di Stefano, A., La Corte, A., and Scatá, M. (2014). A dynamic context-aware multiple criteria decision making model in social networks. In *Information Society (i-Society), 2014 International Conference on*, pages 157–162. IEEE.

Graham, I. D., Logan, J., Harrison, M. B., Straus, S. E., Tetroe, J., Caswell, W., and Robinson, N. (2006). Lost in knowledge translation: time for a map? *Journal of continuing education in the health professions*, 26(1):13–24.

Guermah, H., Fissaa, T., Hafiddi, H., Nassar, M., and Kriouile, A. (2013). Context modeling and reasoning for building context aware services. In *Computer Systems and Applications (AICCSA), 2013 ACS International Conference on*, pages 1–7. IEEE.

Gui, N., De Florio, V., Sun, H., and Blondia, C. (2011). Toward architecture-based context-aware deployment and adaptation. *Journal of Systems and Software*, 84(2):185–197.

Guy, T. V., Karny, M., and Wolpert, D. (2015). *Decision Making: Uncertainty, Imperfection, Deliberation and Scalability*, volume 538. Springer.

Hatak, I. R. and Roessl, D. (2015). Relational competence-based knowledge transfer within intrafamily succession an experimental study. *Family Business Review*, 28(1):10–25.

Holt, C. A. and Laury, S. K. (2002). Risk aversion and incentive effects. *American economic review*, 92(5):1644–1655.

Jaccard, P. (1901). *Etude comparative de la distribution florale dans une portion des Alpes et du Jura*. Impr. Corbaz.

Kahneman, D. and Tversky, A. (1979). Prospect theory: An analysis of decision under risk. *Econometrica: Journal of the Econometric Society*, pages 263–291.

La Corte, A., Scatá, M., and Giacchi, E. (2011). A bio-inspired approach for risk analysis of ict systems. In *Computational Science and Its Applications-ICCSA 2011*, pages 652–666. Springer.

Lambiotte, R. and Panzarasa, P. (2009). Communities, knowledge creation, and information diffusion. *Journal of Informetrics*, 3(3):180–190.

Lazarsfeld, P. F., Merton, R. K., et al. (1954). Friendship as a social process: A substantive and methodological analysis. *Freedom and control in modern society*, 18(1):18–66.

Luo, S., Du, Y., Liu, P., Xuan, Z., and Wang, Y. (2015). A study on coevolutionary dynamics of knowledge diffusion and social network structure. *Expert Systems with Applications*, 42(7):3619–3633.

Nonaka, I. (1994). A dynamic theory of organizational knowledge creation. *Organization science*,5(1):14–37

Pentland, A. (2014). *Social Physics: How Good Ideas Spread-The Lessons from a New Science*. Penguin.

Polanyi, M. (1967). The tacit dimension.

Schilit, B. and Theimer, M. (1994). Disseminating active map information to mobile hosts. *Network, IEEE*, 8(5):22–32.

Suwa, M., Scott, A. C., and Shortliffe, E. H. (1982). An approach to verifying completeness and consistency in a rule-based expert system. *Ai Magazine*, 3(4):16.

Tasselli, S. (2015). Social networks and inter-professional knowledge transfer: The case of healthcare professionals. *Organization Studies*, page 0170840614556917.

Wang, S. and Noe, R. A. (2010). Knowledge sharing: A review and directions for future research. *Human Resource Management Review*, 20(2):115–131.